Comparing Traditional Methods and Digital Platforms for Delineating Management Zones: A Study of Efficiency and Accuracy

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Abstract

Digital platforms have emerged as user-friendly tools to support management zone delineation and field monitoring in precision agriculture. However, the algorithms and methods embedded in these platforms may overlook agronomic and operational constraints, limiting their effectiveness in decision-making. This study evaluated the performance of three commercial digital platforms for management zone delineation and compared them with a reference protocol (Córdoba et al., 2016) and an open-access GIS-based approach (Smart-Map) using variance reduction (%) across multiple seasons. The analysis was conducted in two commercial fields located in Campo do Meio, Minas Gerais, Brazil, using yield data from soybean, corn, and sorghum crops collected over three growing seasons and off-seasons between 2018 and 2021. Satellite-derived vegetation indices and topographic information were integrated to delineate management zones using time-series data. The results showed that delineation performance was primarily driven by the magnitude and spatial structure of field variability rather than by algorithm choice. Fields exhibiting well-structured spatial patterns resulted in greater consistency among platforms, whereas complex or weakly structured variability reduced delineation effectiveness. Increasing the number of management zones did not consistently improve variance reduction or operational suitability, highlighting limitations of commonly used clustering metrics. Overall, the findings demonstrate *that reliable management zone delineation depends less on algorithmic complexity and more on capturing stable spatial variability relevant to agronomic decision-making.*

Keywords. *Clustering, Precision Agriculture, Satellite imagery, Variance Reduction.*

Introduction

Management zones are subareas within a field that exhibit similar agronomic characteristics and are used to represent spatial variability for site-specific management (Gavioli et al., 2016; Gavioli et al., 2019). Delineating fields into zones with comparable attributes contributes significantly to crop management by accounting for spatial heterogeneity and reducing input losses associated with fertilization, seeding, and chemical applications (Gavioli et al., 2016). However, the complex interactions among soil properties that influence crop yield impose limitations on the use of individual input variables, such as nutrients or water availability, as sole indicators of spatial variability (Gili et al., 2017).

In this context, yield maps and satellite-derived vegetation indices have been widely recognized as promising data sources for characterizing field variability (Mulla, 2013; Gili et al., 2017). Satellite imagery offers free and frequent observations suitable for time-series analyses, enabling the identification of consistent spatial patterns within fields. Yield maps integrate the combined effects of physical, biological, and chemical management practices, providing a comprehensive representation of crop performance (Horbe et al., 2013; Gili et al., 2017). These data-driven approaches support precision agriculture by facilitating large-scale field operations and improving input efficiency, thereby increasing profitability (Albornoz et al., 2018). Despite their potential benefits for environmental sustainability, production costs, and net returns, the adoption of technologies to map spatial and temporal variability remains limited among farmers.

Spatial and temporal variability play a fundamental role in crop growth and development, and uniform input application in heterogeneous fields often constrains yield potential. Accurately identifying spatial patterns requires complex data processing workflows, including pre-processing, interpolation, dimensionality reduction, and temporal analysis, which are computationally intensive and time-consuming (Albornoz et al., 2018; Wang et al., 2025). These technical demands represent a major barrier to the widespread adoption of management zone delineation methods.

To address these challenges, user-friendly tools such as Management Zone Analyst (MZA) (Fridgen et al., 2004), R-based protocols (Córdoba et al., 2016), and GIS plugins such as Smart-Map (Pereira et al., 2022) have been developed to generate management zones using remote sensing, yield, and topographic data (Albornoz et al., 2018; Zeraatpisheh et al., 2022; Georgi et al., 2017). However, these approaches often require advanced computational resources and specialized statistical and GIS expertise, limiting their practical use. Recent advances in connectivity, including 5G networks and the Internet of Things (IoT), have enabled the development of web-based platforms capable of integrating large datasets and providing decision-support tools through intuitive interfaces.

Digital platforms offer simplified solutions for analyzing field variability by integrating multiple algorithms within user-friendly environments. Nevertheless, many of these platforms overlook agronomic and operational constraints, resulting in management zones that are poorly suited for field machinery and practical applications (Ali et al., 2022; Gavioli et al., 2019; Wang et al., 2025). In addition, commonly used clustering performance metrics may fail to reflect agronomic relevance, leading to zone delineations that inadequately represent field variability (Sun et al., 2025; Albornoz et al., 2017). Evaluating the performance of digital platforms is therefore essential to build confidence in their application and to support the adoption of site-specific management practices, such as variable-rate seeding, fertilization, and field monitoring. Thus, the objective of this study was to evaluate three commercial digital platforms for management zone delineation and compare their performance with a reference protocol (Córdoba et al., 2016) and an open-access GIS-based approach (Smart-Map), using variance reduction (%) across multiple seasons.

Materials and Methods

Study site description

The study was conducted in two commercial fields located in Campo do Meio, Minas Gerais, Brazil, at 21°06′19″ S and 45°46′09″ W, with an altitude of 778 m. According to the Köppen classification, the climate of the study area is Cwa, characterized as a dry-winter subtropical climate, with temperatures below 18 °C in winter and hot summers with temperatures above 22 °C (Peel et al., 2007).

Yield data

Areas 1 and 2 were used to investigate spatial yield variability across different growing seasons and off-seasons. In Area 1, yield data were collected from soybean crops during the 2018/2019 and 2020/2021 growing seasons and from sorghum during the 2020 off-season. In Area 2, yield data were collected from soybean crops during the 2020/2021 and 2021/2022 growing seasons and from corn during the 2021 off-season. The growing seasons occurred from October to February, whereas the off-seasons occurred from March to August.

Yield data were collected using a John Deere S540 combine equipped with a GreenStar 3 (GS3) ® monitor connected to a Global Navigation Satellite System (GNSS). The monitor was configured to record yield, grain moisture, and elevation data every 3 s. Grain yield values were corrected to 13% moisture content using Equation 1.

$$P_{corrected} = P \times \frac{100-H_1}{100-13} \qquad \text{(Equation 1)}$$

where $P_{corrected}$ represents the grain weight corrected to 13% moisture content, P represents the actual grain weight, and H_1 represents the actual grain moisture content.

However, the yield monitor data still contained outlier values caused by harvester maneuvers, sensor errors, and operational errors. Therefore, following the methodology described by Maldaner et al. (2022), two filters were applied: a global filter followed by a local filter. After filtering, a regular grid with points spaced 40 m apart and a 10 m buffer was created to extract mean values for each growing season and off-season in Area 1 (315 points) and Area 2 (207 points).

Satellite imagery acquisition and vegetation index

The satellite images used in this study were obtained from the Sentinel-2 orbital platform. Images were downloaded using Google Earth Engine (GEE), selecting dates with no cloud cover during the growing seasons and off-seasons (Table 1).

Table 1. Satellite images downloaded from Google Earth Engine (GEE) using the Sentinel-2 orbital platform during the growing seasons and off-seasons.

Date	Area 1			Area 2		
	Soybean	Sorghum	Soil	Soybean	Corn	Soil
2018/19	12/18/2018 01/12/2019 01/22/2019 02/01/2019					
2019		05/07/2019 05/12/2019 05/22/2019 05/27/2019 06/01/2019 06/06/2019 06/11/2019 06/26/2019 07/11/2019 07/21/2019 07/26/2019 07/31/2019 08/10/2019 08/15/2019	04/02/2019			04/22/2019
2019/2020	07/01/2020					
2020		05/06/2020 05/21/2020 05/26/2020 05/31/2020 06/20/2020 06/25/2020 07/05/2020 07/10/2020 07/15/2020 07/20/2020 07/25/2020 07/30/2020				
2020/21	01/21/2021			01/21/2021 01/31/2021		
2021					04/26/2021 05/01/2021 05/11/2021 05/26/2021	

		06/05/2021
		06/10/2021
		06/20/2021
		06/25/2021
	12/27/2021	
2021/22	01/21/2022	
	01/26/2022	

After downloading the satellite images, the Enhanced Vegetation Index (EVI) was calculated (Equation 2) (Jiang et al., 2008). The EVI was used because it improves sensitivity in areas with high biomass and reduces the influence of aerosol effects and canopy background. This is important because vegetation indices such as the Normalized Difference Vegetation Index (NDVI) may be less sensitive under high leaf biomass conditions and may present limitations due to nonlinearity (Rouse et al., 1973; Justice et al., 1998).

$$EVI = \frac{G\ x\ (NIR - RED)}{(NIR + C1 \times Red - C2 \times Blue + L)} \qquad \text{(Equation 2)}$$

The EVI represents the Enhanced Vegetation Index, G represents the gain factor of 2.5, L represents the canopy background adjustment factor of 1, and C1 and C2 represent the aerosol resistance coefficients of 6 and 7.5, respectively.

In addition, the EVI time series was used to identify the date with the most favorable soil background conditions, and the Soil Brightness Index (BI; Equation 3) was then calculated for the corresponding scenes. Specifically, for each area, the date with the minimum EVI value was selected to compute BI. The BI was originally developed to map variations associated with soil moisture, organic matter on the soil surface, and salt content (Escadafal, 1989).

$$BI = \sqrt{\frac{(R^2 + G^2)}{2}} \qquad \text{(Equation 3)}$$

In addition to the vegetation index (EVI) and soil index (BI), elevation data were also used to characterize both areas. Elevation data were obtained from the Shuttle Radar Topography Mission (SRTM) through Google Earth Engine (GEE), with a spatial resolution of 90 m. The processed vegetation indices and elevation data were exported from GEE and imported into QGIS 3.28® to perform the subsequent analyses.

Delineation of management zones

The three digital platforms evaluated in this study delineate management zones based on remote sensing data, such as vegetation indices, elevation, and soil brightness. These data are commonly analyzed as time series, allowing the platforms to identify spatial patterns across growing seasons and off-seasons. The resulting variability maps are then combined with soil brightness and elevation data to determine stable zones within the fields. The efficiency of the digital platforms for management zone delineation was compared with traditional approaches. In

QGIS, raster layers of EVI, BI, and elevation were converted into vector polygons, and mean values were calculated for each satellite image. These layers were then used to generate management zones for Areas 1 and 2 using the Smart-Map plug-in (Pereira et al., 2022). In parallel, management zones were delineated in RStudio version 4.4.1 following the protocol described by Córdoba et al. (2016). For both traditional approaches, QGIS/Smart-Map and RStudio, the number of management zones was set to 3 and 5 to allow direct comparison with the zones obtained from the digital platforms.

Data analysis

Descriptive analyses

Descriptive analyses were performed for each area, crop season, and off-season. Mean, maximum, minimum, standard deviation, and coefficient of variation (CV) values were calculated. The CV was used as an indicator of yield spatial variability.

Variance Reduction in MZ

The variance reduction index (VR%; Equation 4) was used to assess within-zone homogeneity and compare the performance of the digital platforms (Dobermann et al., 2003). This index measures the reduction in variance within management zones relative to the variance of the entire field. Values close to 100% indicate better delineation performance, values close to 0% indicate low reduction in heterogeneity, and negative values indicate that within-zone variance is greater than field-level variance.

$$VR\ (\%) = \left(\frac{\sum_{I=1}^{C} W_I \times V_{mzi}}{Vfield}\right) \times 100 \qquad \text{(Equation 4)}$$

where c represents the total number of MZs, Wi denotes the proportion of the total area for each individual MZ, Vmzi corresponds to the variance of the data within each specific MZ, and Vfield represents the variance of the dataset for the whole field.

Results

Yield varied among crops and growing seasons. The highest mean yield was observed for soybean in the 2020/2021 growing season, with a mean value of 4.79 t ha^{-1}, whereas the lowest yield was observed for sorghum, reaching 2.46 t ha^{-1} (Figure 1). The coefficient of variation differed among growing seasons and off-seasons. The lowest coefficient of variation was observed for soybean in 2020/2021, with a value of 12.39%, indicating lower spatial variability across the field. However, sorghum in 2019 showed the highest coefficient of variation (32.15%), with minimum and maximum yield values of 0.45 and 5.75 t ha^{-1}, respectively. These results suggest that, during this off-season, crop conditions reduced yield and increased spatial variability.

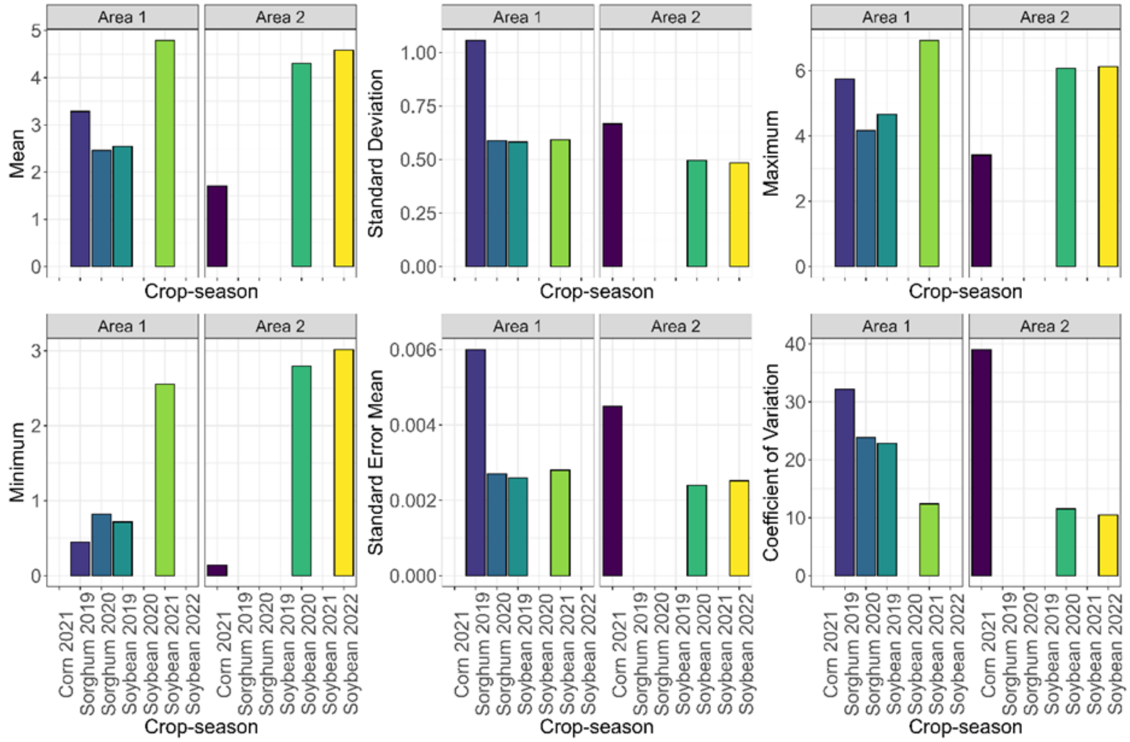

Figure 1. Descriptive analysis of yield (t ha⁻¹) across different crop seasons and off-seasons in Areas 1 and 2.

The soybean yield time series showed a notable increase from 2019/2020 to 2020/2021, with mean yield values increasing from 2.55 to 4.79 t ha⁻¹, representing an increase of approximately 87% (Figure 1). In contrast, sorghum yield decreased from 3.28 t ha⁻¹ in 2019 to 2.46 t ha⁻¹ in 2020, representing a decrease of approximately 25%.

In Area 2, yield showed low variation between the 2020/2021 and 2021/2022 soybean growing seasons. During the 2020/2021 season, soybean yield reached 4.30 t ha⁻¹ and increased by approximately 7% compared with 2021/2022. In contrast, corn yield in the 2021 off-season reached 1.71 t ha⁻¹, likely due to weather conditions, representing approximately 40% of the yield observed for soybean in both seasons. Low coefficient of variation values were observed for soybean, with 11.53% and 10.50% in 2020/2021 and 2021/2022, respectively, whereas corn in 2021 showed a high coefficient of variation (38.99%). This high variability was associated with the wide range of yield values observed during this season, with a minimum of 0.45 t ha⁻¹ and a maximum of 3.41 t ha⁻¹.

Management zones

The performance of the digital platforms for management zone delineation was evaluated by comparison with the protocol developed by Córdoba et al. (2016), the Smart-Map approach in QGIS (Pereira et al., 2022), and three commercial platforms, referred to as A, B, and C (Figure 2). Although the same input data were used to evaluate all methods, the digital platforms showed different segmentation patterns compared with the reference method.

Compared with Area 2, Area 1 showed greater spatial variability, as confirmed by the coefficient of variation values obtained from the yield data (Figure 1). The Córdoba et al. (2016) protocol produced spatially coherent zones, and its delineation was compatible with agricultural machinery operations. In addition, Platform A, Smart-Map, and the reference protocol showed comparable spatial patterns. In contrast, Platform B delineated zones with smoother boundaries. Platform C produced the poorest delineation for Area 1 in both the 3- and 5-zone configurations. Its maps showed strong spatial fragmentation, with many small pixel-sized zones that created a “salt-and-pepper” effect, characterized by small patches within larger zones and low spatial continuity. This pattern compromised the operational use of the zones for machinery and field management.

In Area 2, which exhibited more structured variability with a well-defined east–west gradient, stronger methodological agreement was observed. The reference protocol, Platform B, and Smart-Map converged toward visually similar solutions, partitioning the field without the appearance of small and fragmented zones. This result indicates that, when the main source of spatial variation is dominant and well defined, such as yield potential evaluated over several seasons or elevation, most of the tested algorithms are sufficiently robust to identify it correctly. However, Platform C was an exception, showing a more diffuse pattern and less clearly defined boundaries between zones.

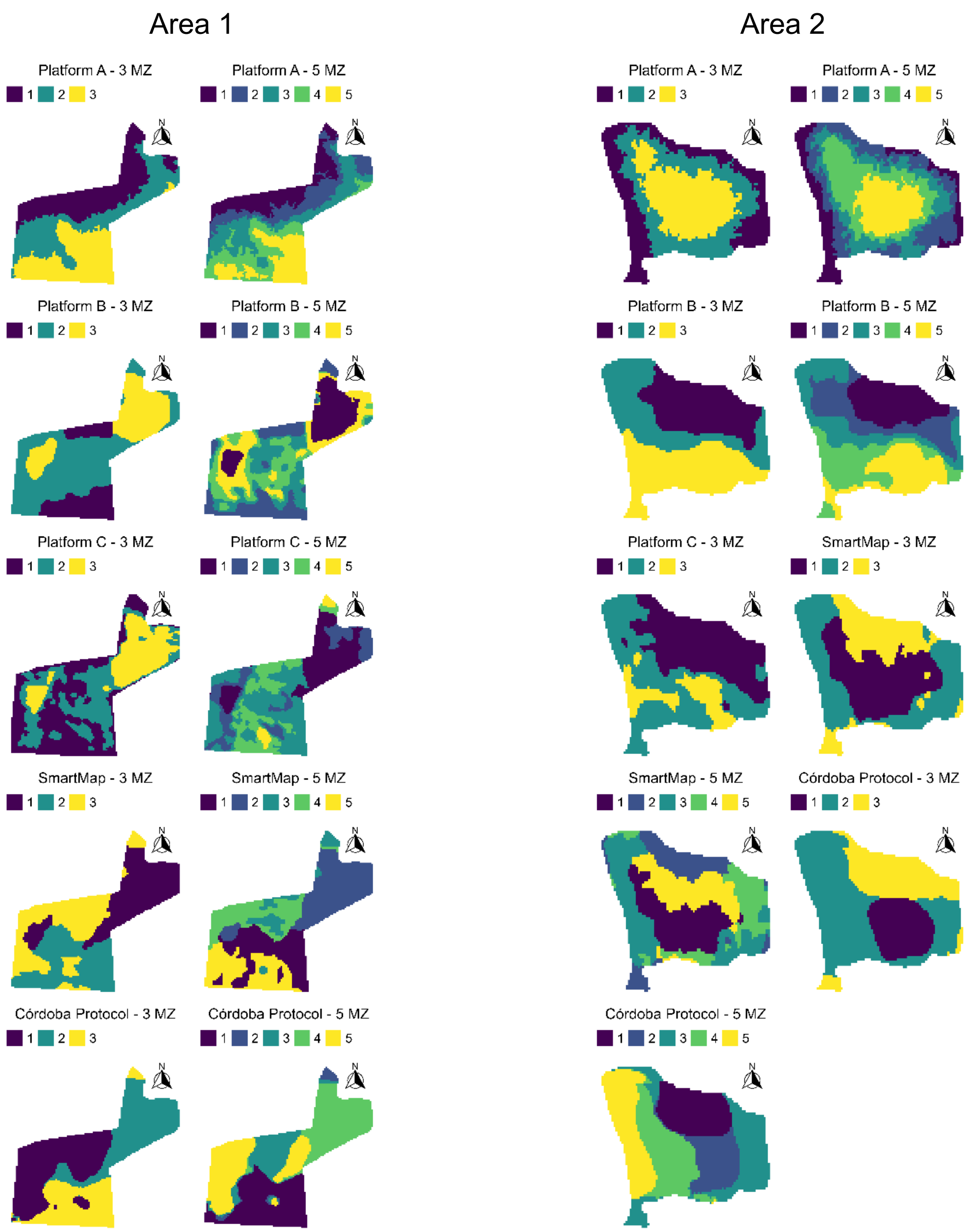

Figure 2. Management zones generated by integrating yield data, EVI, and BI values, comparing three digital platforms (A, B, and C) with two reference methods: Smart-Map and the Córdoba et al. (2016) protocol.

Increasing the number of MZs from 3 to 5 allowed the reference protocol to identify a low-yield-potential zone in Area 1 that had been overlooked in the 3-MZ delineation. However, the three evaluated platforms (A, B, and C) and the Smart-Map method produced more segmented maps, which reduced their interpretation and agronomic usefulness due to lower spatial continuity. In contrast, in Area 2, even when the number of MZs was increased for site-specific applications, all evaluated methods generated a reasonable number of management zones. These results indicate that increasing the number of MZs affected delineation performance and that each algorithm responded differently to spatial variability. Therefore, selecting the most appropriate platform requires considering both spatial and agronomic coherence.

Variance Reduction (VR)

The analysis of management zone (MZ) delineation efficiency using the Variance Reduction index (VR%) revealed clear differences among the evaluated tools, indicating that the choice of platform directly affected the homogeneity of the management units (Figure 3).

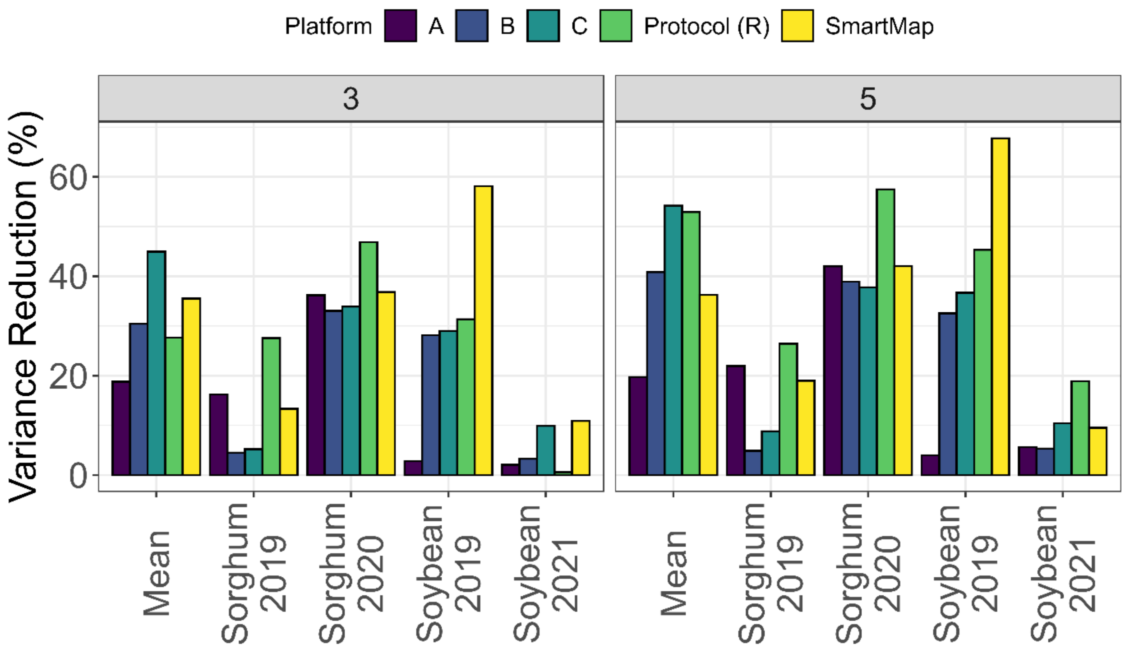

Figure 3. Variance reduction values for each crop season and off-season from 2019 to 2021 in Area 1, considering sorghum and soybean crops.

Considering the consolidated mean values, the reference methods, Smart-Map and Protocol (R), established the highest performance threshold, achieving the greatest variance reduction values, particularly in the 5-zone scenario, where they surpassed 50% VR. Among the commercial platforms, Platform C showed the best average performance, approaching the reference methods and visibly outperforming Platforms A and B at both segmentation levels. This behavior indicates that the algorithm used by Platform C was more effective at minimizing within-zone variance relative to total field variance, thereby contributing to the creation of more homogeneous management zones.

For the sorghum crop, the results showed temporal variation in the response of the evaluated platforms. In the 2019 sorghum season, overall VR% values were more modest, with Protocol (R) and Platform C maintaining the highest performance, while Platform B showed one of the lowest efficiencies in the study. This indicates that the delineation for that season resulted in limited reduction in heterogeneity. In contrast, in the 2020 sorghum season, delineation quality improved for nearly all methods. Protocol (R) and Smart-Map achieved high VR% values, suggesting that sorghum yield spatial variability in 2020 was more structured and better aligned with the management zones generated by the platforms. Platform A also improved compared with the previous year, but remained below the other methods, reinforcing its limitation in converting field heterogeneity into more uniform zones.

Platforms A and B showed the lowest average VR% values, indicating inefficient delineation across several scenarios. Platform A had the lowest partitioning capacity, maintaining low VR% values even when the number of zones increased from 3 to 5. This suggests an algorithmic limitation in capturing and organizing the spatial variability of the data. Increasing the number of zones from 3 to 5 generally improved efficiency for all methods, as expected, since field fragmentation tends to reduce internal residual variance. However, this improvement was more pronounced for Smart-Map and Platform C, reinforcing the better performance of these tools in refining the zoning process.

Despite the differences among methods, marked temporal instability was observed, especially in the Soybean 2021 season. In that year, all platforms showed VR% values near or below 10%, indicating low delineation efficiency, where the division into zones failed to adequately isolate variability. This suggests that, in seasons where variability is governed by random or external factors not captured by the model, the comparative advantage among platforms is reduced. However, in years with greater spatial structure, such as the sorghum seasons and Soybean 2019, Smart-Map, Protocol (R), and Platform C were the most robust options, producing more uniform zones and greater reliability for variable-rate input prescription.

In contrast to the higher efficiency observed in Area 1, Area 2 showed substantially lower delineation performance. Mean VR% values rarely exceeded 25%, suggesting that spatial variability in this area was more erratic or less influenced by the stable soil factors used by the platform algorithms (Figure 4). Although the reference methods, Smart-Map and Protocol (R), remained among the best-performing approaches, their values were modest compared with Area 1, reaching around 20% even in the refined 5-zone scenario.

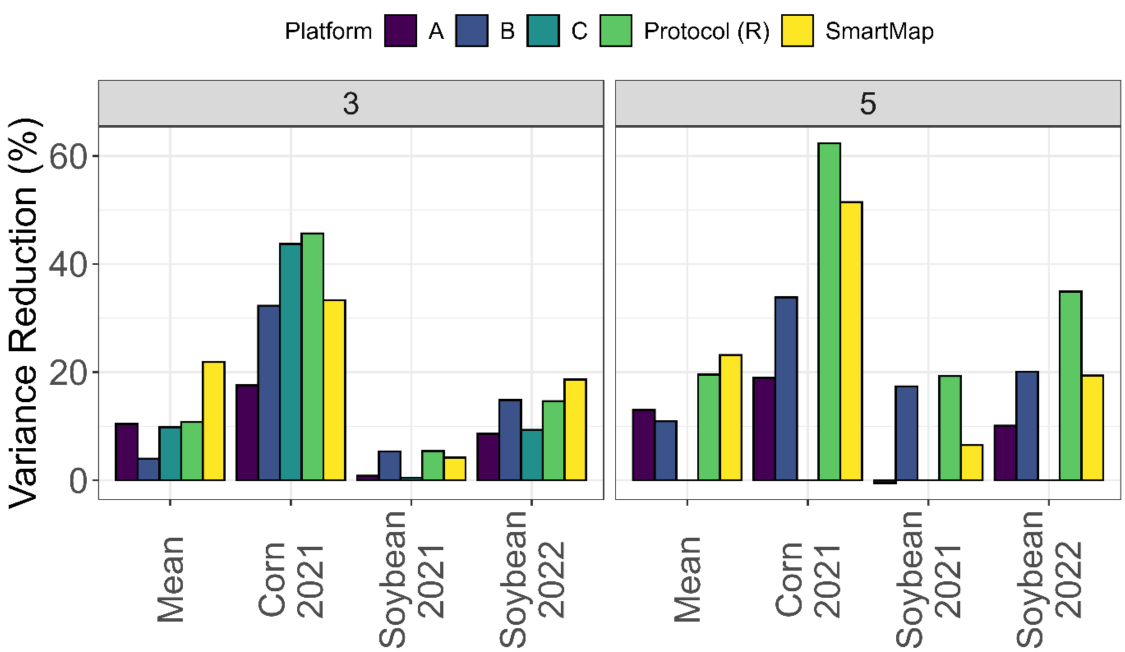

Figure 4. Variance reduction values for each crop season and off-season from 2021 to 2022 in Area 2, considering corn and soybean crops.

The crop-specific analysis in Area 2 highlighted the distinct behavior of the Corn 2021 season. In this scenario, superior and divergent performance was observed. For the 3-MZ delineation, Protocol (R) and Platform C showed the best results, with VR values of 45.65% and 43.74%, respectively, followed by Smart-Map (33.3%), Platform B (32.27%), and Platform A (17.56%). When the number of MZs was increased to 5, Protocol (R) and Smart-Map achieved peak VR values of 62.33% and 51.44%, respectively, indicating highly effective delineation for corn during that year. Descriptive analysis also showed that Corn 2021 had the highest coefficient of variation (CV = 38.99%). This suggests that, although high field-scale variability offers greater opportunity for variance reduction, it also requires higher algorithmic precision to successfully capture the spatial structure.

Conversely, performance declined markedly during the soybean seasons. In Soybean 2021, VR% values approached zero for nearly all platforms. According to Dobermann et al. (2003), values close to 0% indicate that delineation provides low reduction in heterogeneity, making the adoption of variable-rate technology (VRT) technically questionable for that specific cycle. Among the commercial tools, Platform C, which stood out in Area 1, showed unstable performance in Area 2. It even reached 0% VR in the 5-zone Corn 2021 scenario and was outperformed by Platform B in Soybean 2022. Platform A consistently recorded the lowest values, including negative VR% values for Soybean 2021 in the 5-zone model. Mathematically, negative VR indicates that within-zone homogeneity was lower than field-level homogeneity, evidencing a critical failure in the partitioning algorithm for this area.

The data from Area 2 reinforce that platform efficiency is highly dependent on both season and crop. The low temporal stability of VR% in these fields suggests that caution is needed when recommending static management zones, as delineation efficiency varied substantially according to the spatial structure of each specific harvest.

Discussion

Spatial variability directly influences decisions related to fertilization, seeding rates, and chemical input management, affecting both environmental sustainability and economic returns (Guastaferro et al., 2010). The results of this study indicate that the effectiveness of management zone delineation was more strongly associated with the magnitude and spatial organization of field variability than with the choice of algorithm alone. In crop seasons characterized by pronounced climatic influence, such as sorghum 2019 and corn 2021, elevated coefficient of variation and variance reduction values reflected unstable spatial patterns, which altered the consistency of zone delineation across methods. These findings support the idea that a limited number of seasons may fail to capture persistent spatial structures, potentially leading to suboptimal delineation strategies (Ali et al., 2022; Silva, 2006). Furthermore, integrating yield data with vegetation indices improved the ability of algorithms to discriminate spatial patterns compared with single-source inputs, reinforcing the importance of multivariate approaches for management zone delineation (Ali et al., 2022). Methods that explicitly account for spatial autocorrelation and the multivariate nature of agricultural systems tended to produce zones with greater spatial coherence (Gili et al., 2017). Similar findings were reported by Song et al. (2009), who observed high agreement (Kappa = 0.91) when combining soil properties and yield data, whereas reliance on remote sensing data alone resulted in substantially lower agreement (Kappa = 0.16), highlighting the limitations of univariate approaches.

Descriptive statistics provided an initial overview of the input variables but were insufficient to characterize the spatial organization of field variability relevant to management zone delineation.

Fields with high CV values posed greater challenges, particularly when variability lacked a consistent spatial structure, emphasizing that descriptive metrics alone cannot capture spatial patterns. Although CV values are useful indicators of within-field heterogeneity, they do not describe how variability is spatially distributed, which is critical for defining stable management zones. Previous studies have reported that high CV values are often associated with increased field heterogeneity, as observed by Zeraatpisheh et al. (2022) when delineating management zones based on soil properties and nutrients. However, high CV values, such as those observed for corn in 2021 in Area 2 (>35%), likely reflect the influence of transient and uncontrolled factors, including weather conditions, which disrupt spatial stability and reduce the effectiveness of zone delineation. These results suggest that high variability driven by short-term environmental effects may obscure persistent spatial patterns, leading to poorer management zone definition.

Digital platforms play a key role in translating complex spatial data into actionable information for field monitoring and decision-making. In this study, methods that explicitly incorporated spatial continuity and agronomic reasoning generated management zones that were more compatible with field operations, whereas excessive spatial fragmentation limited their practical applicability despite increased algorithmic complexity. Fragmented delineations, characterized by small and irregular zone shapes, restrict machinery operation and reduce the feasibility of site-specific management, a limitation widely reported in the literature (Albornoz et al., 2018). The definition of the number of management zones further influenced delineation quality and operational usefulness. Previous studies have emphasized that the number of zones should be selected according to management objectives and map quality rather than algorithmic output alone (Gili et al., 2017). In this context, delineations based on three zones generally produced more coherent and operationally feasible patterns than those based on five zones, particularly when increased segmentation resulted in a “salt-and-pepper” effect, as observed for Platform C. Such effects are commonly associated with clustering approaches that inadequately constrain spatial continuity, leading to disjointed and irregular zones (Albornoz et al., 2018). Several strategies have been proposed to improve zone delineation and optimize the number of clusters, including the use of performance indices such as the Fuzziness Performance Index (FPI) and Modified Partition Entropy (MPE) (Fridgen et al., 2004; Boydell and McBratney, 2002), which have been successfully applied under different agricultural conditions (Gavioli et al., 2016; Jovanovic et al., 2025). Consistent with these findings, the present study showed that increasing the number of management zones enhanced variance reduction only under well-structured spatial variability, indicating that higher spatial segmentation does not necessarily translate into improved agronomic decision-making. In fields with dominant and stable spatial patterns, such as Area 1, the delineations produced by different platforms converged toward similar spatial configurations, whereas in more complex fields, increased segmentation reduced spatial coherence.

Variance reduction proved useful for comparing management zone delineation approaches. However, its limitations as a standalone performance metric were evident. Although widely applied to assess zone quality, low VR values do not necessarily indicate field homogeneity, but may reflect constraints in capturing small or temporally unstable spatial variability. Consequently, a single metric may oversimplify the assessment of management zone performance, reinforcing the need to combine quantitative indicators with spatial coherence and agronomic interpretability. From an operational perspective, disregarding small-scale spatial variability may lead to inefficient input allocation, underscoring the relevance of management zone delineation even in fields with relatively low yield variability. In this context, the present study compared the performance of different digital platforms with a reference protocol (Córdoba et al., 2016) and an open-access GIS-based implementation (Smart-Map). The results revealed convergence among platforms in fields with well-structured spatial variability (Area 1), whereas delineation performance declined under more complex and weakly structured variability conditions (Area 2). A key limitation of management zone delineation identified in this study relates to data availability, as short temporal records may be insufficient to capture persistent spatial patterns required for reliable delineation.

Future research should therefore focus on integrating longer multi-season datasets and developing algorithms capable of consistently identifying stable spatial structures while minimizing irregular, fragmented, or disjointed zone shapes. Such advances are essential to improve the operational feasibility of management zones and support the development of robust, generalizable models for site-specific management.

Conclusion

The results demonstrate that the efficiency of MZ delineation, measured by variance reduction (VR%), is highly dependent on both the algorithm used and the inherent spatial structure of each crop season.

The R protocol and Smart-Map provided the most consistent and reliable delineations. For commercial adoption, Platform C offered a competitive alternative, whereas Platforms A and B showed lower efficiency and occasional algorithmic failures, as indicated by negative VR values. These findings suggest that practitioners should prioritize platforms that demonstrate consistently high VR% values across multiple years before adopting static variable-rate management strategies.

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